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Short term complex hydro thermal scheduling using integrated PSO-IBF algorithm

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ABSTRACT

In this article, an integrated evolutionary technique such as particle swarm optimization (PSO) algorithm and improved bacterial foraging algorithm (IBFA) have been developed to provide an optimum solution to the scheduling problem with complex thermal and hydro generating stations. PSO algorithm is framed based on the intelligent behavior of the fish school and a flock of birds and the optimal solution in the multidimensional search region is achieved by assigning a random velocity to each potential solution (called the particle). BFA is designed by following the prey-seeking (chemotactic) nature of E. coli bacteria. This technique is followed in an improved manner to get the convergence rate in dynamic for a hyperspace problem by implementing a chemotactic step in a linearly decreased way instead of the static one. The effectiveness of this integrated algorithm is evaluated by using it in a complex thermal and hydro generating system. In this testing system, multiple numbers of cascaded reservoirs in hydro plants have a time coupling effect and thermal power units have a valve point loading effect. The simulation results indicate its merits by comparing it with other meta-heuristic techniques related to the fuel cost required to generate the thermal power.

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1. INTRODUCTION

In this modern world, the demand for electricity is increased due to its widespread utility. To meet the load requirement, by considering the availability of fossil fuel and water, more number of thermal power plants and hydropower stations are employed in the power system network. Thus, scheduling these generating stations in an optimal manner is very important in terms of operating costs. Since the operating cost required for hydropower plants is considered to be the lowest value, this scheduling problem is mainly focused on reducing the fuel cost of thermal generating units considering the major constraints for both types of power plants. In this hydrothermal scheduling (HTS) problem, the system includes the key constraints such as the timing effect of the cascaded reservoirs of the hydro system, different water inflows into the reservoirs for the planning period, turbine flow rate and reservoir storage limitations, variation in load demand and limits on power generation capacity.

In previous years, the HTS problem has been solved by classical methods considering the number of simple assumptions to obtain an efficient search operation. It is suggested in [1] an algorithm based upon an augmented lagrangian relaxation approach developed in conjunction with the decomposition and coordination method to resolve the problem of short-term hydrothermal generation scheduling (STHTS) with environmental and transmission network constraints. Using the Lagrangian relaxation technique, the STHTS problem is solved by dividing it into thermal and hydro sub-sections [2]. In this technique, Lagrangian multipliers are updated using the dynamically constrained cutting plane method. A two-level dynamic programming (DP) algorithm is given in [3] to solve the long-term planning problem of the thermal and hydroelectric generating system with multiple reservoir configurations. An effective non-linear programming technique is described to achieve optimum results for a complex thermal and hydro scheduling problem in a short period of time [4]. These conventional methods are well documented and are widely used in different formulations to solve scheduling problems and provide effective results for smooth cost equations. Furthermore, certain drawbacks, such as difficulties in handling constraints, dimensional difficulties, more computation time, and trapping into local optimum are observed.

Over the past few decades, meta-heuristic search algorithms were developed to overcome these shortcomings and find the optimal solution. A coarse-grained parallel simulated annealing (SA) algorithm is demonstrated to attain an optimal solution for the STHTS problem [5]. An integrated simulated annealing and genetic algorithm approach has been proposed to solve the STHTS problem with multiple thermal plants [6]. A new evolutionary programming (EP) algorithm is developed with Gaussian mutation to resolve the short-term thermal and hydro planning problems [7]. A Gaussian and Cauchy mutations-based EP technique is developed and tested in complex hydro and thermal power plants having restricted operating zones [8]. An interactive fuzzy satisfying approach based on the EP algorithm is utilized to solve multi-objective short-term complex hydrothermal planning problems [9]. Orero and Irving have applied a multi-step genetic algorithm (GA) to obtain the foremost solution for thermal and hydro planning problems with connected reservoirs [10]. GA based on the diploid genotype model is employed to achieve an optimal solution to the STHTS problem [11]. The STHTS problem is spliced into three sub-problems such as hydrothermal coordination, unit commitment, and economic load dispatch, and solved the problem by using GA [12]. An enhanced GA with specified genetic operators is presented to resolve the problem of thermal and hydro scheduling [13]. Ramirez and Onate used GA to achieve the best solution to the thermal and hydroelectric planning problem, which was divided into three subdivisions [14]. A novel cultural approach (CA) to find the most favorable solution to the thermal and hydro planning problem, in which the planned period was taken as one day and each interval time as one hour [15]. A hybrid differential evolution (DE) technique is developed in conjunction with an equality constraint handling process to attain the best solution for the STHTS problem with various significant constraints [16]. These stochastic search techniques have received significant attention because they are easier to implement, derivative-free, robust, and often involve a limited number of parameter tunings. However, a few shortcomings such as large computational time, slow convergence towards an optimal solution, and local optimization are noticed when applied in large dimensional and nonlinear problems.

In recent years, swarm optimization techniques have been used extensively due to the nature of its data sharing and transfer process. Amid swarm optimization techniques, PSO and BFA are the most favorable to attain the optimal solution to a complex power system problem. The PSO algorithm is introduced for optimizing a broad spectrum of functions [17]. The performances of EP-based algorithms and PSO techniques are demonstrated in solving the STHTS problem [18]. The scheduling problem of the thermal and hydroelectric systems having numerous constraints is resolved by employing different PSO approaches [19]. The PSO technique is presented to attain the most favorable solution to a complex hydrothermal generating system scheduled for one day [20]. PSO in an improved quantum behaved manner is implemented to resolve short-term combined economic emission thermal and hydro scheduling problems [21]. And the STHTS problem is resolved by employing a specific repair process, a small population-based PSO algorithm, and other operations such as mutation, DE–acceleration, and migration [22]. An Improved self-adaptive PSO algorithm is provided in [23] to solve the STHTS problem. In this technique, two functions such as effective adjustment of the two responsive parameters of PSO and randomness adjustment in various constraints are carried out to obtain the optimal solution to the hydro thermal planning problem. The BFA is introduced to solve various optimization problems [24]. An improved BFA is developed to resolve the classic thermal and hydro planning problem [25]. A modified PSO with the impact of BFA on the problem of constrained dynamic economic dispatch is applied in [26].

The PSO technique is very much efficient in implementing and constraining parameters and has consistent convergence characteristics for optimal resolution. It bears the capability to find almost global solutions to hydrothermal planning problems. In this technique, a small number of free adjustable parameters are taken to achieve the desired goal. Also, this technique is utilized to attain optimal parameter values in various fields of the power system. Furthermore, a literature study of PSO reveals that this technique is sometimes implicated in local optimization. BFA is utilized effectively to resolve the problem of non-linear hydrothermal planning. But, when utilized for a wide range of HTS problems, it exhibits poor convergence behavior and more timing requirements. Hence in this algorithm, a decreasing effective function is used to enhance the convergence properties.

In this scheduling problem, an integrated approach to both the PSO and IBF algorithm is applied to the test system [20], thus exploiting the benefits of both algorithms when attempting to compensate for the shortcomings of individual techniques. This integrated algorithm monitors a consistently varying solution of the composite cost functions with reliability and precision. This combined technique delivers output within a short calculated time. The integrated PSO-IBFA has efficient investigative and exploitative capabilities in the search process and several cases avoid premature and incorrect convergence. The advantage of this approach is manifested by examining the results with other optimization techniques. The subsequent sections are described in the following fashion. Section 2 elaborates on the mathematical model of the experimental system, including constraints such as equality and inequality. The proposed integrated PSO–IBFA approach is expressed in section 3. Section 4 reports the simulation outcome of this integrated method. Section 5 outlines the conclusions.

2. PROBLEM FORMULATION

2.1. Objective function

Hydroelectric generating units have zero incremental costs, so the main purpose of this complex hydroelectric thermal power planning problem is focused on reducing the operating cost required for a thermal plant by observing equality and inequality limitations.

The fuel cost and valve point loading characteristics of thermal generator is formulated as follows:

$$\min(f) = \sum_{m=1}^{M} . \sum_{i=1}^{N_s} \left[a_{si} + b_{si} P_{sim} + c_{si} P_{sim}^2 + \left| d_{si} \times sin\left\{ e_{si} \times \left(P_{si}^{min} - P_{sim} \right) \right\} \right| \right] \quad (1)$$

2.2. Equality limitations:

(a) During the planning period, at every time interval, actual power produced by the entire plant should meet the load power demand.

$$\sum_{i=1}^{N_s} P_{sim} + \sum_{j=1}^{N_h} P_{hjm} - P_{Dm} = 0, \quad m \in M \quad (2)$$

(b) Power generated by the hydroelectric plant is expressed as a function of reservoir volume and water release rate and is stated as follows:

$$P_{hjm} = C_{1j} V_{hjm}^2 + C_{2j} Q_{hjm}^2 + C_{3j} V_{hjm} Q_{hjm} + C_{4j} V_{hjm} + C_{5j} Q_{hjm} + C_{6j}, j \in N_h, m \in M \quad (3)$$

(c) The hydraulic continuity equation for water reservoir is as follows.

$$V_{hjm} = V_{hj(m-1)} + I_{hjm} - Q_{hjm} - S_{hjm} + \sum_{l=1}^{R_{uj}} \left[Q_{hl(m-t_{lj})} + S_{hl(m-t_{lj})} \right], \ j \in N_h, \ m \in M \quad (4)$$

(d) The spillage rate is considered to be zero in equation (4). Hence, hydraulic continuance limitations are stated as follows:

$$V_{hj0} - V_{hjM} = \sum_{m=1}^{M} Q_{hjm} - \sum_{m=1}^{M} \sum_{l=1}^{R_{uj}} Q_{hl(m-tlj)} - \sum_{m=1}^{M} I_{hjm}, \ j \in N_h, \ m \in M \quad (5)$$

(e) The water release rate of hydroelectric unit 'j' at dependent interval "d" is estimated by considering the constraints such as water release values and preliminary and ultimate reservoir storage conditions.

$$Q_{hjd} = V_{hj0} - V_{hjM} + \sum_{m=1}^{M} I_{hjm} + \sum_{m=1}^{M} \sum_{l=1}^{R_{uj}} Q_{hl(m-tlj)} - \sum_{\substack{m=1 \\ m \neq d}}^{M} Q_{hjm}, \ j \in N_h, \quad (6)$$

(f) Thermal power generation for a dependent thermal power plant d_g is evaluated by observing the power balance limitations.

$$P_{sd_g m} = P_{Dm} - \sum_{\substack{i=1 \\ i \neq d}}^{N_s} P_{sim} - \sum_{j=1}^{N_h} P_{hjm}, \quad m \in M \quad (7)$$

2.3. In equality constraints:

(i) Thermal generation limits:

$$P_{si}^{min} \leq P_{sim} \leq P_{si}^{max},\ i \in N_{s,}\ m \in M \tag{8}$$

(ii) Hydro generation limits:

$$P_{hj}^{min} \leq P_{hjm} \leq P_{hj}^{max},\ j \in N_{h,}\ m \in M \tag{9}$$

(iii) Reservoir storage limits:

$$V_{hj}^{min} \leq V_{hjm} \leq V_{hj}^{max},\ j \in N_{h,}\ m \in M \tag{10}$$

(iv) Water discharge rate limits:

$$Q_{hj}^{min} \leq Q_{hjm} \leq Q_{hj}^{max},\ j \in N_{h,}\ m \in M \tag{11}$$

3. INTEGRATED PSO-IBF ALGORITHM

The control parameter values have been assigned to the PSO-IBF algorithm. In the PSO algorithm, reservoir volume is taken as particle position to circumvent convergence in a similar region and to evade local minima. In this PSO technique, the fitness value is evaluated using the fuel cost equation of the thermal power stations. The effectiveness of BFA is enhanced by modifying the constant chemotaxis step to a linearly decreasing way using a dynamic function. In this integrated approach, the final population of the PSO is provided to the IBFA as the initial population.

3.1. PSO Algorithm

PSO technique was put forward by James Kennedy and Russell Eberhart (1995), which is utilized to resolve continual, non-linear, and multi-modal optimization problems based upon swarm intelligence such as fish school, birds flock, and human societal conduct. In this technique, the problem is solved by a search process performed by individuals in a population called particles. These particles are indicated as the best possible solution to the optimization problem. Initially, the particles assigned in the population are randomly generated. At every iteration process, the velocity (V_j^k) and position (x_j^k) of each particle are updated, taking into account the previous best (pbest) and global best (gbest) values. The equations are formulated as follows:

$$V_j^{k+1} = WV_j^k + c_1 rand_1(\,)\left(pbest - x_j^k\right) + c_2 rand_2(\,)\left(gbest - x_j^k\right) \tag{12}$$

$$x_j^{k+1} = x_j^k + K * V_j^{k+1} \tag{13}$$

Where V_j^k is the j^th^ particle velocity located on k^th^ iteration and ‘W’ indicates the parameter for inertia weight.

$$W = W_{max} - \frac{W_{max} - W_{min}}{iter_{max}} * iter \tag{14}$$

Where W_{min}= 0.4, W_{max} = 0.9, $iter_{max}$ indicates the maximal number of iterations and iter denotes the current number of iterations.

c_1 and c_2 denote the acceleration constants,
c_1 = 2, c_2 =2

$$K = \frac{2}{\left[2 - \phi - \sqrt{\phi^2 - 4\phi}\right]} \tag{15}$$

Where $\phi = c_1 + c_2$ and $\phi \geq 4$

'K' depicts the constriction factor. $rand_1()$ and $rand_2()$ represent the random value assigned uniformly between 0 and 1.

3.2. Implementation of PSO algorithm:

1. The particles of the population are randomly initialized by satisfying all thermal and hydro power plant limitations.
2. The initial fitness value is considered as pbest and gbest values.
3. The velocity of the particle is initialized arbitrarily between $[V_{max}, V_{min}]$.
4. New 'V' of the particle is updated using equation (12).
5. Velocity is checked with threshold limit. If "V" exceeds the limit, then the velocity limit is fixed.
6. New particle position value is updated using equation (13).
7. A dependent time interval is chosen for an unknown particle position value.
8. Thermal generation, hydro generation, and water discharge rate for nondependent time intervals are calculated.
9. The Water release rate and volume of the reservoir are calculated at a dependent time interval.
10. Hydro and thermal power generation are calculated at dependent time interval by using step 9.
11. Thermal and hydro constraints are checked and fitness value is calculated.
12. The fitness (pbest and gbest) values are updated.
13. The procedure from step 4 to step 12 is repeated until the last iteration.
14. The latest gbest value generated by the particle indicates the resolution of the problem.

3.3. IBF Algorithm

BFA is a heuristic optimization approach motivated by the food searching nature of Escherichia coli (E. coli) bacteria. The life-style of E.coli bacteria such as the foraging strategy, decision-making mechanism, and moving nature was illustrated by Kevin M. Passino (2002). BFA is formatted to deal the problems having complicated and non-differentiable target functions. Three major functions such as chemotaxis, regeneration, and removal/dispersal actions are performed to locate the solution area [24]. The chemotaxis action of the bacteria is activated by two functional methods such as swimming and tumbling. By switching between these two modes of operation the bacteria contribute throughout its lifespan. In this algorithm, a tumble is denoted by a constant length in a random path, and φ (j) indicates the moving direction of the bacteria after a tumble. The bacteria move in an inconsistent path, which is referred to by the constant run-length unit $C(i, j)$. In the bacterial group, the position of i^{th} bacteria at the j^{th} chemotactic step, k^{th} regeneration step, and l^{th} removal/ dispersal occurrence is noted by $\theta^i(j, k, l) \in \Re^p$. In this bacterium position, the cost function, also referred to as nutriment function, is expressed as $J(i, j, k, l)$. The location of the i^{th} bacterium after a tumbling action is referred to as

$$\theta^i(j+1, k, l) = \theta^i(j, k. l) + C(i, j)\Phi(j) \tag{16}$$

At this location, the cost function $J(i, j+1, k, l)$ is evaluated, and if this value is lower $J(i, j, k, l)$, one more step $C(i, j)$ is executed in a similar direction. This swimming process is continued until the low cost is gained and a maximum number of steps "N_s" are attained. Bacteria group release cell-to-cell signaling $J_{cc}(\theta, P)$ effect to form swarm patterns that affect the cost function of every bacterium in the group. This swarming function is represented in the following equation:

$$J_{cc}(\theta, P(j, k, l)) = \sum_{i=1}^{S} J_{cc}^{i}\left(\theta, \theta^i(j, k. l)\right)$$

$$= \sum_{i=1}^{S}\left[-d_{attract}\exp\left(-w_{attract}\sum_{m=1}^{p}(\theta_m - \theta_m^i)^2\right)\right] + \sum_{i=1}^{S}\left[-h_{repellant}\exp\left(-w_{repellant}\sum_{m=1}^{p}(\theta_m - \theta_m^i)^2\right)\right] \tag{17}$$

Where $d_{attract}$, $w_{attract}$, $h_{repellant}$ and $w_{repellant}$ denote the parameters that indicate the behavior of attractant signals and repellent signals emitted by the cell. The position (θ) of component 'm' in the bacterium 'i' is indicated as θ^i_m. Here, $P(j,k,l)$ denotes the location of the respective member in the bacteria group 'S' and is expressed as:

$$P(j,k,l) = \{\theta^i(j,k.l)|i = 1,2,\ldots,S\} \tag{18}$$

Where 'S' denotes the total members in the bacteria group.

Then, cell-to-cell signaling function [$J_{cc}(\theta,P)$] and the cost function are added.

$$J(i,j,k,l) + J_{cc}(\theta,P) \tag{19}$$

After the maximum chemotactic steps have reached (N_C), a reproduction process is executed. The bacterial population is halved by the destruction of less healthy bacteria. Each healthiest bacterium in the remaining half is divided into two so as to maintain the same population.

$$S_r = S/2 \tag{20}$$

After N_{re} number of reproduction process, N_{ed} numbers of elimination or dispersal occurrences are carried out. In this activity every bacterium can be transferred to reveal other sections of the search space. The possibility for every bacterium to undergo the removal or dispersal process is decided by a pre-assigned fraction p_{ed}. In BFA, the chemotaxis process has a constant run-length unit which might ensure favorable search results for minor optimization problems. Contrarily, it exhibits poor performance when implemented for complicated wide-ranging problems with high dimensions. The run-length parameter is mainly contributed to control the local and global search capability of this algorithm. Therefore, BFA is improved by proposing a decreasing dynamic function for the chemotaxis process, thus a balanced exploration and exploitation search process is achieved. It is stated as follows:

$$C(i,j) = C(N_C) + \left(C(1) - C(N_C)\right)\left(\frac{N_C - j}{N_C}\right) \tag{21}$$

Where 'j' denotes the chemotactic step, N_C indicates chemotactic steps in maximum value, and $C(N_C)$ and $C(1)$ are predetermined parameters.

3.4. Implementation of IBF algorithm

1. The following parameters such as the population of bacteria(S), search space dimension(p), chemotactic steps count$(N_{c)}$, swim length(N_S), regeneration process count(N_{re}), removal-dispersal occurrences count (N_{ed}), removal/dispersal probability of the bacterium(p_{ed}), initial run-length unit$C(i,j)|_{j=1}$, run-length unit until the last chemotactic step $C(N_C)|_{j=N_C}$, and arbitrary location of every bacterium at the beginning (θ^i) are initialized.
2. Removal or spreading loop is executed, $l = l + 1$
3. Reproduction loop is carried out, $k = k + 1$
4. Chemotaxis loop is performed, $j = j + 1$

For $i = 1,2,3,\ldots,S$, the chemotaxis process is activated for every bacterium in the following manner: Cost function $J(i,j,k,l)$ is estimated using (17) and (19).

Let $J_{last} = J(i,j,k,l)$ thus affordable cost can be detected.

Tumble: An arbitrary vector $\Delta(i) \in \Re^p$ is generated, and $\Delta_m(i)$, where m = 1, 2, 3 …, p denotes an arbitrary number between 0 and 1.

$\Phi(i)$ is calculated as: $$\Phi(i) = \frac{\Delta(i)}{\sqrt{\Delta^T(i)\Delta(i)}} \tag{22}$$

Move: The location of the bacterium is found by using (16).

Cost function $J(i,j+1,k,l)$ is computed and by applying swarming equation (17). $J_{cc}\big(\theta,P(j+1,k,l)\big)$ is computed. Then new cost function $J(i,j+1,k,l)$ is found out by using equation (19).

Swim: let $m = 0$ (counter swim length)

While $m < N_S$ (no climbing down for long time)

Let $m = m + 1$

If $J(i, j+1, k, l) < J_{last}$, let $J_{last} = J(i, j+1, k, l)$.

Then further step is taken in the same direction. And new cost function $J(i, j+1, k, l)$ is evaluated.

Else, let m =Ns. This is the end of the while statement.

Go to the subsequent bacteria ($i = i + 1$ if $i \neq S$)

Dynamic decreasing function (run length unit) is updated by using equation (21).

5. If $j < N_C$ go to the step 4 ($j = j + 1$). At this point, chemotaxis process continues till the lifetime of the bacteria.
6. Regeneration process is started:

By considering 'k' and 'l', the healthiness of every bacterium 'i' is assessed in the following way:

$$J^{i}_{health} = \sum_{j=1}^{N_c+1} J(i, j, k, l) \tag{23}$$

The health of the i^th bacterium refers to the number of nutrients it receives in its lifetime. Bacteria are arranged in ascending order according to their accumulated cost [J^{i}_{health}]. Higher the cost (high J_{health}) indicates the least healthy bacterium. Half of the bacterial population (S) with the highest J_{health} values computed from equation (20) die, and in the other half (S_r), each bacterium divides into two and takes the same place as their parental bacteria.

7. If $k < N_{re}$, go to step 3, (k= k+1).
8. Removal or dispersal loop is executed.

With probability P_{ed}, *the* elimination and dispersal process takes place for every bacterium to maintain a consistent value of population size.

9. If $l < N_{ed}$, then go to step 2 ($l = l + 1$), if not, stop.

4. SIMULATION RESULTS

To verify the possibility and efficacy of this integrated PSO-IBF algorithm, it has been implemented into a standard testing system adopted in previous works [20] and resolved using MATLAB software. The test system comprises three thermal power stations having a valve point loading effect and four multi-chain cascaded hydro plants with a time coupling effect. The scheduling period for hydrothermal plants has been assigned as 24-time slots with a one-hour interval for each time slot. Spillage rate and transmission line loss are presumed to be zero. The configuration of hydro reservoirs and its water time delay data matrix is displayed in figure 1. The power demand data, power production parameters of hydro plant, hydro reservoir inflows, hydro plant data with power generation limits, and cost curve parameters with generation limits of thermal plants are shown in tables 1 – 5 respectively.

Table 1. Load demand data

Time slot	Demand (MW)	Time slot	Demand (MW)	Time slot	Demand (MW)
1	750	9	1090	17	1050
2	780	10	1080	18	1120
3	700	11	1100	19	1070
4	650	12	1150	20	1050
5	670	13	1110	21	910
6	800	14	1030	22	860
7	950	15	1010	23	850
8	1010	16	1060	24	800

Table 2. Hydroelectric power production coefficients

Plant	C_1	C_2	C_3	C_4	C_5	C_6
1	-0.0042	-0.42	0.030	0.090	10.0	-50
2	-0.0040	-0.030	0.015	1.14	9.5	-70
3	-0.0016	-0.30	0.014	0.55	5.5	-40
4	-0.0030	-0.31	0.027	1.44	14.0	-90

Table 3. Hydro plant reservoir inflows ($\times 10^4$ m^3)

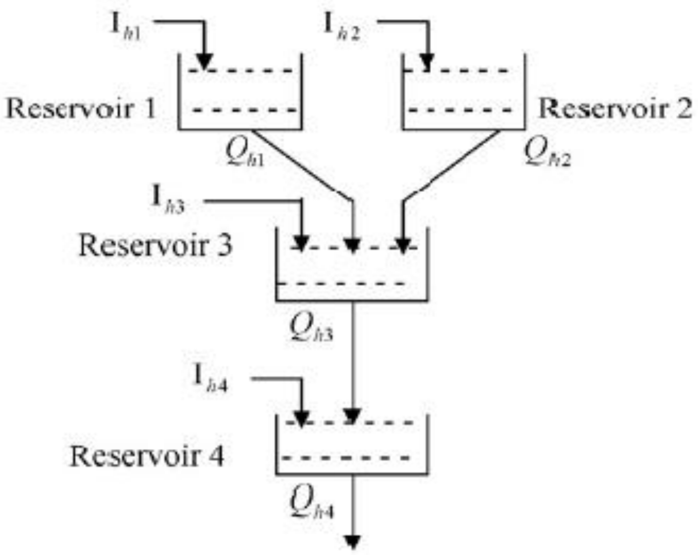
Time slot	Reservoir inflows 1	2	3	4	Time slot	Reservoir inflows 1	2	3	4	Time slot	Reservoir inflows 1	2	3	4
1	10	8	8.1	2.8	9	10	8	1	0	17	9	7	2	0
2	9	8	8.2	2.4	10	11	9	1	0	18	8	6	2	0
3	8	9	4	1.6	11	12	9	1	0	19	7	7	1	0
4	7	9	2	0	12	10	8	2	0	20	6	8	1	0
5	6	8	3	0	13	11	8	4	0	21	7	9	2	0
6	7	7	4	0	14	12	9	3	0	22	8	9	2	0
7	8	6	3	0	15	11	9	3	0	23	9	8	1	0
8	9	7	2	0	16	10	8	2	0	24	10	8	0	0

Table 4. Hydro plant data ($\times 10^4\, m^3$) and generation limit (MW)

Plant	V^{min}	V^{max}	V_{ini}	V_{end}	Q^{min}	Q^{max}	P_h^{min}	P_h^{max}
1	80	150	100	120	5	15	0	500
2	60	120	80	70	6	15	0	500
3	100	240	170	170	10	30	0	500
4	70	160	120	140	6	20	0	500

Table 5. Cost curve factors and thermal power production limits

Unit	a_s (\$ / h)	b_s (\$ / (MW h)	c_s (\$ / (MW)^{2}h)	d_s (\$ / h)	e_s (1MW^{-1})	P_s^{min} (MW)	P_s^{max} (MW)
1	100	2.45	0.0012	160	0.038	20	175
2	120	2.32	0.0010	180	0.037	40	300
3	150	2.10	0.0015	200	0.035	50	500



Where I_{hj} : Water inflow to jth reservoir

Q_{h_j} : Water discharge of jth plant

Plant	1	2	3	4
R_u	0	0	2	1
t_d	2	3	4	0

R_U : No of overhead units
t_d : Delay time to immediate lower down unit

Figure 1. Hydraulic system data

Table 6 displays the PSO parameters value. The optimal thermal and hydro and power generation schedule and water release rate of the PSO algorithm are displayed in tables 7 – 8.

Table 6. Values of parameters used in PSO

Parameters	Values
Variable size	24
Size of the population	100
Maximal inertia weight	0.9
Minimal inertia weight	0.4
Particle cognitive learning element c1	2.0
Particle social learning element c2	2.0

Table 7. Hydro thermal generation schedule using PSO

Hour	P_{h1}	P_{h2}	P_{h3}	P_{h4}	P_{s1}	P_{s2}	P_{s3}	Cost($)
1	48.80	43.83	27.61	32.80	43.83	201.32	351.81	
2	81.65	51.69	38.15	63.65	51.70	109.05	384.10	
3	232.63	56.07	33.29	222.63	56.07	43.90	65.41	
4	39.59	45.45	41.78	19.59	45.46	292.95	55.18	
5	115.58	71.04	30.23	104.58	71.04	213.65	63.90	
6	53.17	46.98	37.48	40.17	46.98	62.78	500.44	
7	23.24	26.05	55.35	6.25	26.05	294.61	258.45	
8	43.86	49.95	76.58	27.86	49.95	42.43	499.37	
9	179.34	46.68	28.28	169.35	46.68	251.47	368.19	
10	59.12	57.45	42.74	46.12	57.45	41.59	497.54	
11	78.40	72.81	37.44	67.40	72.81	299.70	51.44	
12	20.30	31.72	42.86	5.30	31.72	51.93	496.16	45150.36
13	179.38	54.76	36.58	165.39	54.76	185.64	433.50	
14	181.03	54.93	87.25	163.03	54.93	62.54	426.30	
15	179.10	42.08	28.01	169.10	42.08	145.48	404.16	
16	58.25	51.62	29.96	47.25	51.62	298.56	312.72	
17	205.87	41.87	48.79	188.88	41.87	189.86	332.85	
18	32.84	38.99	25.71	22.84	38.99	41.85	498.78	
19	281.27	54.41	33.26	271.27	54.42	228.26	147.11	
20	109.96	52.85	57.50	91.96	52.85	58.66	496.22	
21	280.98	72.56	35.90	264.98	72.56	107.02	75.99	
22	40.32	62.13	38.52	24.32	62.13	230.14	402.45	
23	184.63	19.07	27.52	172.63	21.07	289.59	87.50	
24	55.51	54.01	82.73	40.51	54.02	40.45	482.76	

Table 8. Hourly plant discharge (m^3) using PSO

Hour	Q_{h1}	Q_{h2}	Q_{h3}	Q_{h4}
1	78372	121398	183208	60049
2	137663	68109	164420	101251
3	141256	72529	193619	97751
4	140927	130244	256256	100204
5	66603	75307	139388	71426
6	53777	89349	102869	103204
7	61078	87693	242446	109048
8	106238	124048	229209	66142
9	56216	107178	189262	60159
10	59116	124813	283099	63114
11	56061	64412	190765	61928
12	114853	79424	287809	102755
13	55767	115788	191307	130267
14	119821	67836	284615	88306
15	105186	117148	244402	67643
16	53487	101422	236050	61212
17	79829	126929	101270	148227
18	89920	73936	205990	77645
19	68962	111278	181321	111206
20	127416	126409	221153	73843
21	96647	134975	204411	70279
22	57334	90640	142711	120013
23	114359	75235	219441	60070
24	133996	83145	275166	131678

The cost ($) obtained by using the PSO algorithm is 45150.36. The effect of cost characteristics derived from the PSO technique is shown in figure 2 and it is identified that with fewer iterations, this algorithm converges to the optimum value. Thus the PSO approach is considered optimal in terms of feasibleness and processing time.

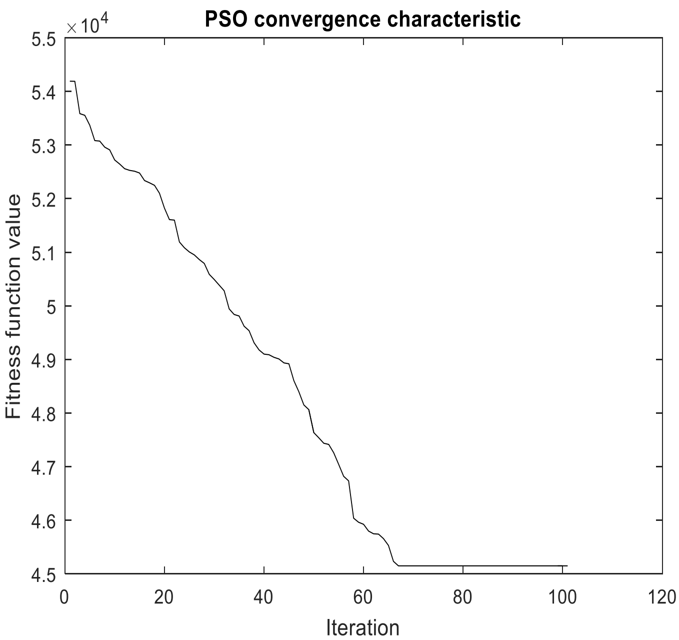


Figure 2. PSO convergence characteristics

Table 9 displays the values of parameters applied in the IBFA.

Table 9. Values of parameters used in IBFA

Parameters	Values
Search space dimension	24
Bacterial population	20
Chemotactic steps count	20
Swimming length	4
Reproduction step count	4
Elimination-dispersal count	24
Number of bacterial reproductions (splits)	$S_r = s/2$
Probability value assigned to each bacterial elimination/dispersal process	0.25

Tables 10 - 11 display the power station production schedule and water release rate of the IBF algorithm.

Table 10. Hydro thermal generation schedule using IBFA

Hour	P_{h1}	P_{h2}	P_{h3}	P_{h4}	P_{s1}	P_{s2}	P_{s3}	Cost($)
1	53.66	81.37	176.77	146.83	43.97	94.29	153.11	43095.46
2	144.22	40.89	104.24	206.79	174.59	42.64	59.63	
3	140.38	29.00	140.52	119.10	173.28	55.87	53.85	
4	72.08	89.08	83.97	94.72	53.84	100.26	156.05	
5	136.99	70.33	52.29	75.18	173.26	46.03	82.92	
6	58.03	156.32	132.67	127.20	80.06	150.53	95.19	
7	195.40	70.97	74.92	142.03	123.97	137.22	205.49	
8	107.69	143.16	155.75	226.23	174.09	80.72	80.36	
9	120.48	178.05	183.65	136.63	110.35	145.05	215.78	
10	124.29	136.21	231.32	203.09	122.97	225.60	56.51	
11	114.85	89.55	208.09	173.97	174.94	214.07	84.53	
12	232.45	56.08	133.42	282.51	125.44	238.17	81.93	
13	165.93	296.95	117.83	120.91	85.76	110.72	211.90	
14	131.47	208.73	111.32	191.85	123.92	142.40	120.30	
15	65.37	119.32	170.95	153.85	152.84	191.46	156.20	
16	118.50	214.83	149.82	30.09	173.76	69.35	243.66	
17	257.30	127.26	170.53	165.80	79.55	148.53	101.02	
18	202.15	118.30	72.27	142.61	121.35	221.48	241.84	
19	38.46	272.93	152.24	247.78	79.30	252.42	56.87	
20	186.49	223.38	70.06	175.37	90.08	77.01	227.59	
21	128.40	140.24	112.83	88.05	114.31	160.32	165.84	
22	94.55	171.96	180.64	97.56	85.01	46.21	184.08	
23	127.05	108.97	139.18	138.71	143.85	113.06	79.18	
24	91.61	130.80	93.76	83.83	160.67	156.10	83.24	

Table 11. Hourly plant discharge (m^3) using IBFA

Hour	Q_{h1}	Q_{h2}	Q_{h3}	Q_{h4}
1	101475	135906	251909	168981
2	77927	118728	293914	199325
3	149115	61717	242266	72015
4	149400	130456	270770	155470
5	98595	132409	178166	198668
6	100500	157111	117751	164086
7	141568	113181	283043	159325
8	82492	99237	226343	72394
9	125297	84801	277376	80196
10	149021	110925	299718	184181
11	78637	99742	215134	153906
12	99427	83627	114766	197832
13	148036	90506	130956	190870
14	127629	105661	179411	195094
15	88595	123302	207018	182613
16	142506	123793	123770	166118
17	134680	127215	150186	185243
18	102244	75666	196325	193166
19	82544	114922	158163	123106
20	115669	102585	240768	100678
21	99616	117856	150474	117057
22	96599	123958	176535	163354
23	99292	63465	166932	195356
24	118683	145491	183706	99919

The final fuel cost value received from the IBF algorithm is 43095.46 $. Figure 3 portrays the cost characteristics obtained from the IBF algorithm. It has been revealed that this algorithm offers the lowest cost value at a faster convergence rate compared to other algorithms.

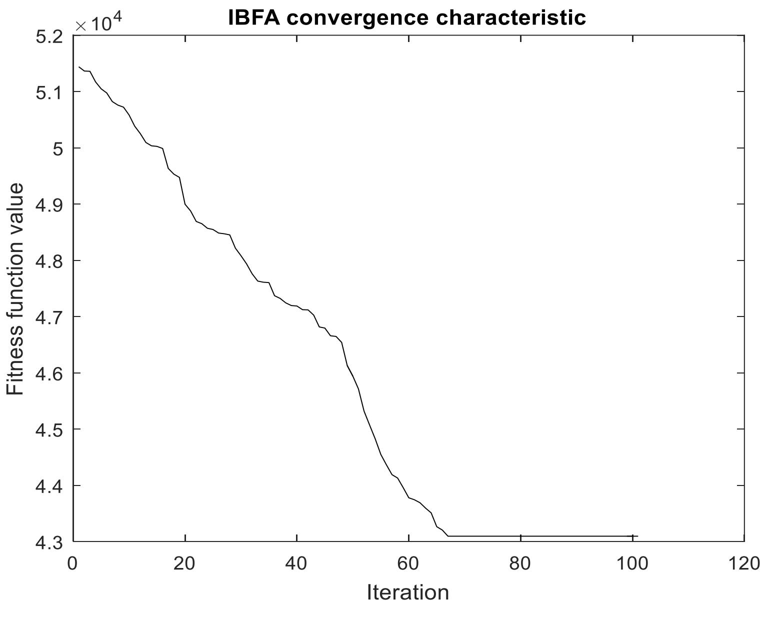


Figure 3. IBFA convergence characteristics

Table 12 provides the comparative results of the proposed integrated approach with other stochastic algorithms.

Table 12. Comparative results of different optimization algorithms

S.No	Authors	Technique	Cost ($)
1	K.K.Mandal. et.al	EP [20]	47,306
2	K.K.Mandal. et.al	SA [20]	45,466
3	K.K.Mandal. et.al	PSO [20]	44,740
4	Balachander. et.al	Proposed PSO-IBFA	43, 095

It is known from the comparative results that the propounded PSO-IBF algorithm bestows a globally optimal solution with minimal calculation time than the other optimization techniques. In this proposed technique, a dynamic decreasing function is applied to update the solution path, thus greatly improving the convergence properties. Hence it is proved that the PSO-IBF algorithm possesses the potential to obtain the best possible solution with nominal time for the complex STHTS problems.

5. CONCLUSION

This paper has successfully implemented a unified PSO-IBFA technique to resolve the complex STHTS problem. Several equality and inequality limitations such as power equivalence constraints, reservoir storage limits, and hydraulic continuity, valve point loading effect, hydro and thermal power generation limits, discharge rate limit, and time coupling effect are taken into account for the experimental system. The PSO algorithm has the robustness to restrict parameters and bears more computational efficiency. In the PSO algorithm, reservoir volume is selected as particle position to circumvent the local minima. In this algorithm, the process of updating the particle position and velocity provides a faster convergence speed to achieve the best solution globally, despite the discontinuities of the cost function. Also, all the particles improve themselves by utilizing the information linked to better particles, so as to enable the swarm diversity. In the IBFA, the chemotactic process is applied to improve the investigation approach. It assists in promptly jumping from local minima and reduces the randomness of the PSO technique in an extensive range system with various limitations. The simulation outcome realizes that the integrated PSO-IBF algorithm outperforms the existing meta-heuristic algorithm for providing a globally optimal solution and executing less computational time. As a future scope, this proposed technique can be utilized to resolve complex thermal, hydro, solar, and wind power planning problems.

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